A New Method for Statistical Downscaling of GCM Precipitation and Application to South Florida Water Management

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1. Water Management in South Florida

❑ South Florida is particularly vulnerable to changes in precipitation due to its unique hydrologic characteristics, high population density, and diverse water resource stakeholders. The native hydrology of southern Florida has been greatly altered through drainage, canalization, urbanization, and agriculture to such an extent that the Everglades are now one of the most threatened ecosystems in the nation (Fig. 1).

❑ The federal government is currently making an effort to restore the Everglades ecosystem with little consideration of how future changes in climate may alter the flow of freshwater into the system. Planning is currently based on an assumption of stationarity using precipitation and temperature data from the historical record (1965-2000), without taking into account the impact of the long-term climate change in response to projected global warming on the regional hydrology.

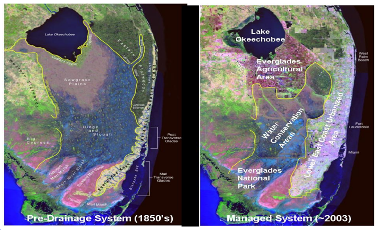


Figure 1: The left panel shows the estimated pre-drainage hydrological system, and the right panel shows the current managed system, which includes diverse stakeholders including agriculture, urban areas, and the Comprehensive Everglades Restoration Plan.

2. Current GCM Projections

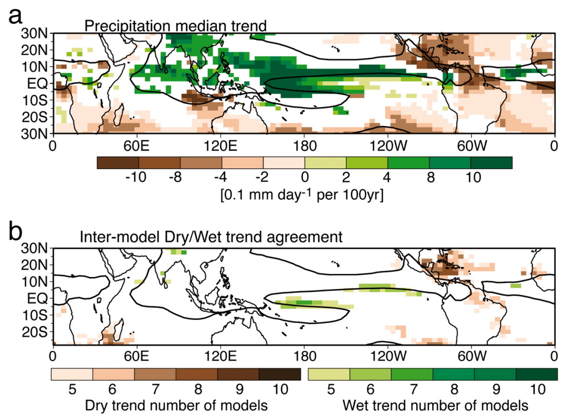
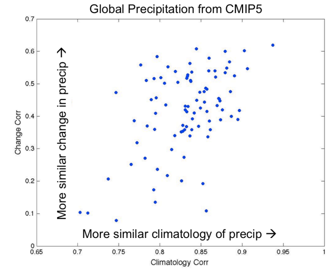


Figure 2: Multi-model local precipitation trend measures. (a) Precipitation trend for JJA of the multi-model ensemble median from 1979 to 2099. Shading indicates >99% significance by the Spearman-rho test. The black line gives the 4 mm/day contour from the median climatolog (1900–1999 average) of the models to indicate a typical boundary of the convection zones. (b Model agreement on the predicted local precipitation trend from 1979 to 2099 for JJA. The number of models at each location that agree on a dry trend or a wet trend exceeding 99% significance and exceeding a minimum amplitude change (20% of the median climatology pe century) is given by the brown or green color bars, respectively. Only regions with five or more o the 10 models agreeing are shaded. From Neelin et al. (2006).



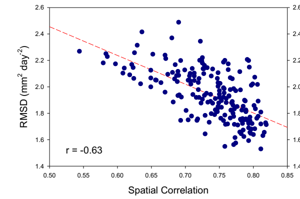


Figure 4: Scatter plot of the RMSD between model-simulated and observed (GPCP) precipitation averaged over the period 1979-2005 against the corresponding spatial correlation over the 60ºS-60ºN domain.

Figure 3: A comparison of the spatial correlation in the base climatology of precipitation between two models (x-axis) with the corresponding spatial correlation in the change in precipitation between those same two models (y-axis). Results are shown for the RCP4.5 scenario from CMIP5. From He and Soden (2016).

❑ A robust decrease in rainfall is projected over the Caribbean and extending into South Florida (Fig. 2). While certain aspects of GCM projections are robust, such as "*wet get wetter*", regional projections often differ among GCMs, in particular, over South Florida (Obeysekera et al., 2011).

❑ Implicit in the "*wet get wetter*" rule of thumb for projections of anthropogenic precipitation change is a dependence of the change in precipitation on the unperturbed climatology. Recent research has further emphasized the importance of the base climatology in influencing the projections of climate change from seasonal to centennial time scales (Figs. 3 and 4).

❑ ***By statistically correcting for biases in the spatial structure of the model's unperturbed precipitation climatology*, we can improve the consistency of model projections of precipitation change at the regional scale.**

3. Pattern-displacement Algorithm for Statistical Downscaling

Biases resulting from the poor representation of topography and land-sea configuration in climate models are rectified by spatially adjusting model-simulated precipitation climatology to satellite observations from TRMM and GPM (e.g., Fig. 5)

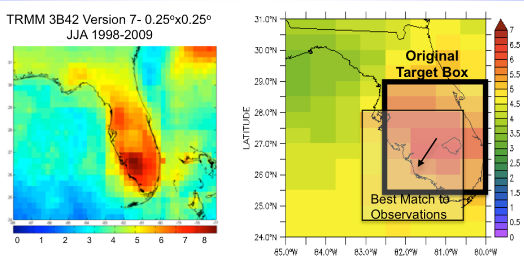
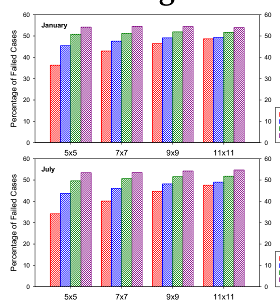


Figure 5: An illustration of the spatial-displacement tracking algorithm (Soden, 1998) applied to GCM simulations from the 0.5º GFDL FLOR coupled ocean-atmosphere forecast model for JJA using TRMM 3B42 observations. Maps display observed and model-simulated precipitation (mm/day).

4. Sensitivity Test for Optimal Pattern Matching



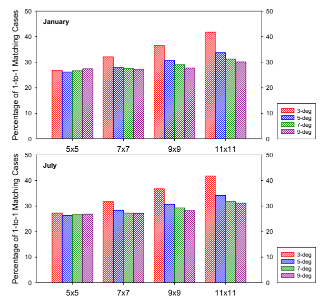


Figure 6: Percentage of failed precipitation pattern matching cases between CCSM4 simulations and GPCP observations over the 60ºS-60ºN domain as a function of the size of the reference and target boxes and the searching distance from the center of the reference box: (top) January and (bottom) July. The units of the size and the distance are in degrees.

Figure 7: Percentage of one-to-one precipitation pattern matching between CCSM4 and GPCP over the 60ºS-60ºN domain as a function of the size of the reference and target boxes and the searching distance from the center of the reference box: (top) January and (bottom) July. Failed cases were filled by interpolation before computing the percentage.

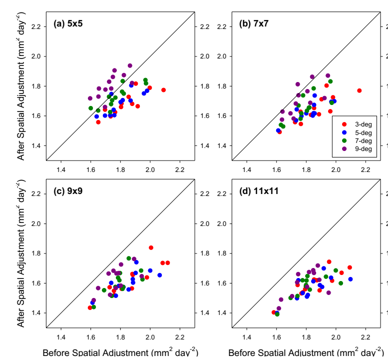


Figure 8: Impacts of the spatial adjustment on root-mean-square difference (RMSD) between GPCP-observed and CCSM4-simulated precipitation over the 60ºS-60ºN domain. The RMSD is computed only for one-to-one pattern matching cases, in which the size of the reference and target boxes ranges from (a) 5º×5º to (d)11º×11º. Individual symbols represent an individual month (January-to-December). The searching distance from the center of the reference box is represented using different colors. The one-to-one line is shown for reference.

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